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Noora Anniina Korhonen

Why do banks fail in Europe? The role of bank-specific and macroeconomic factors

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Author: Noora Anniina Korhonen

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ABSTRACT:

This paper studies bank failures in EU-12 countries before and after the financial crisis of 2007-2008. Logit regression is used to examine how bank specific and macroeconomic factors affect a probability of a bank failure between 2006 and 2012. A behavior of bank specific factors four years before a bank failure is further studied in order to draw conclusions how the variables change over time. Lastly, a number of predicted bank failures before and after 2012 is calculated to see whether the number is decreased since the crisis.

The results show that both bank specific and macroeconomic factors are important when forecasting bank failures. Especially size is a highly significant factor and contrast to the ”too-big-to-fail”, an increase in size increases a probability of a bank failure. Further examining of bank specific variables show that they behave differently over time and certain factors tend to change significantly several years before a failure whereas some change just before a failure. Lastly, even though the analysis shows that a number of predicted bank failures has decreased after the financial crisis, it is not clear whether it is a result of changes in bank regulation and supervision.

Keywords: bank failures, bank distress, bank fundamentals, Europe, logistic regression

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1 Introduction

It has been over ten years since the crash of Lehman Brothers started the worst economic crisis since the Great Depression. During the crisis a large number of banks closed in U.S. and in Europe or they were bailed out by governments in order to stay in business. Because the crisis was big, widespread and expensive, policy makers, academics and researchers have later focused on determining the causes of the crisis in order to prevent it happening again. This has lead to a number of studies which examine the relationship between various factors and a probability of a bank failure (Arena, 2008; Bongini, Claessens, & Ferri, 2001; Lin & Yang, 2016; Poghosyan & Čihak, 2011).

In the history there has been many destructive economic and banking crises, and good examples are the Nordic, Russian and Asian crises in the 1990s as well as the most recent financial crisis in 2008. During the 2007-2008 financial crisis governments were forced to bail out several distressed banks in order to prevent the whole economy from collapsing. For example, the cost of the 2008 financial crisis in Iceland was 43% and in Ireland 41% of the GDP (Laeven & Valencia, 2010).

In normal times bank failures are rare, but during crisis periods they increase significantly (Cleary & Hebb, 2016). Due to a globalization, banks have become more connected and problems in one economy can quickly spread to other economies causing widespread problems. Kaufman (1994) points out that contagion can be even more damaging in a banking system since it occurs faster and results in large losses to creditors at failed banks. In addition to contagious effect, the banks have grown in size causing a ”too-big-to-fail” effect that forced for example governments to bail out certain big banks during the financial crisis in 2007-2008.

Because bank failures can cause big negative effects to economic, it is important to understand what causes these problems in the market. Previous research have focused both on predicting economic crises and individual bank failures (Arena, 2008; Lin & Yang, 2016; Poghosyan & Čihak, 2011; Roy & Kemme, 2012). By studying banking crises, it has been found that certain factors tend to behave similarly before a crisis (Reinhart & Rogoff, 2008). For example, Babecký et al. (2014) and Drehmann and Juselius (2014) find that private credit growth and interest rate tend to increase before a failure. In addition, Babecký et al. (2012) results suggest that also world GDP and inflation are good indicators of banking crises.

In addition to forecasting crises, it is important that policy makers and supervisors focus on preventing individual banks from defaulting and causing bigger problems. Thus, bank failure studies focus on determining which factors affect a probability of a bank failure. It has been found that both macroeconomic factors (such as variables above) and bank balance sheet data are important when forecasting bank failures (Arena, 2008; Lin & Yang, 2016; Poghosyan & Čihak, 2011). The research on both bank failure and banking crisis provides valuable information for policy makers and supervisors that could help them to enhance a stability of banking markets and prevent or at least dampen the next financial crisis.

1.1 Purpose and contribution

The purpose of this study is to determine factors that affect individual bank failures by focusing on both bank specific and macroeconomic variables. In addition to regression analysis, I study deeper how bank specific variables behave before a bank failure. More specifically, I analyze how the variables change over a time period of four years before a failure to a failure year. Determinants of bank failures have been studied widely before, however, their behavior has not been studied at a deeper level, and my aim is to shed more light on this subject. Lastly, I study whether a number of bank failures has decreased after 2012. I examine two time periods, from 2006 to 2012 and from 2013 to 2018, and predict bank failures during both of the periods. The aim of this analysis is to study whether a number of bank failures has decreased after changes in bank supervision and regulation.

This research paper contributes to a bank failure literature by examining EU-12 countries during and after the 2007-2008 financial crisis. Because there are not many studies on bank failures in Europe, and in my knowledge no comprehensive study during and after the financial crisis[1], this paper aims to fill the gap in the research. It is important that European policy makers and supervisors have a deep knowledge on what factors are important when analysing bank's stability, and how these factors behave before a bank is in danger to go bankruptcy. Thus, my analysis could help the policy makers and supervisors to gain better knowledge on bank failures which could enable them to make European banking markets more stable and banks more resilient for future shocks.

1.2 Structure of the paper

After an introduction to the topic, I present a theory of banking crises by Hyman Minsky which aims to explain why banking crises occur. Next, I am presenting a prior empirical evidence on determinants of bank failures and discuss about forecasting methods and predictive accuracy. The rest of the paper focuses on my own empirical analysis. First, I introduce the methodology that I am using. Then, I present my data and finally the results of my empirical analysis. Lastly, I have conclusions.

[1]Forgione and Migliardo (2018) examine Italian banks during and after the financial crisis and use the estimated model to forecast bank failures in other European banks. However, in my knowledge there are no study that would take in account several European countries during and after the crisis.

2 Theory of Banking Crises by Hyman Minsky

This section discusses about Hyman Minsky's writings on financial crises. Minsky was an American economist and his theories have become highly popular after the 2007-2008 financial crisis. He emphasizes increases in debt levels and financial system fragility as an explanation of crises in capitalist markets. Minsky's theories could serve an explanation for the most destructive crisis since the Great Depression that occurred in 2007-2008.

The first chapter discusses about Minsky's writings on financial fragility which is the base of his theory of instability. Second part explains Minsky's probably the most famous theory: Financial Instability Hypothesis. Lastly, Minsky's views on banking are discussed, and in the conclusions everything is wrapped up and his theories are analyzed during the 2007-2008 financial crisis. In addition to Minsky's research papers, I use as a reference a book that discusses about his theories and has been written by his former teaching assistant L. Randall Wray.

2.1 Financial fragility

Hyman Minsky explains the occurrence of financial crises by a systemic fragility. He argues that after the World War II, the U.S. financial system evolved towards more fragile which explains the increase in financial crises after 1960s. After the World War II there was a twenty years period when the system was stable and a possibility of a crisis was low. Based on Minsky's fragility view, the period of prosperity and financial growth increased the system fragility, and made it possible for financial crises to develop. (Minsky, 1977.)

Minsky defines a systemic fragility as a result of a normal functioning of an economy. Furthermore, a fragile financial system can be disrupted by an event which in stable economy would not have any impact but in unstable environment can lead even to a deep depression. Once the systemic fragility has developed, financial crises can occur. Minsky argues that before a deep depression there has to be a financial crisis, and thus, a fragile system will go through a deep depression from time to time. (Minsky, 1977.)

Minsky writes that ”a financial crisis starts when some unit cannot refinance its position through normal channels and is forced to raise cash by unconventional instruments or by trying to sell out its positions.” This is related to three kinds of financing that Minsky defines: hedge finance, speculative finance and ”Ponzi” finance. In a hedge finance, units’ cash flows are enough to meet all of their payment obligations. It is the most stable form of finance since it is not vulnerable to what happens in the financial markets. (Minsky, 1977.)

Units that engage speculative finance can meet their payment commitments (interest payments) but cannot repay the principle with their cash flow. When they have to repay the debt, they are forced to issue new debt. Speculative finance is vulnerable to interest changes and can turn to ”Ponzi” finance if rates rise enough. That way speculative finance is vulnerable to market movements. Banks and governments usually engage this kind of finance. (Minsky, 1977.)

In a ”Ponzi” financing, cash flow is not enough to meet either payment commitments or the principle. Like speculative financing unit, ”Ponzi” unit has to issue new debt or sell equity to meet its obligations. However, ”Ponzi” unit is more unstable than speculative unit and as its share in an economy increases, so does the fragility of the system. ”Ponzi” finance tend to increase during a boom as investors take more risk. (Minsky, 1977; Wray, 2015.)

Other determinants of systemic fragility are liquidity and a level of debt. Speculative and ”Ponzi” finance have to either issue new debt or sell assets in order to meet their payment obligations. If they decide to sell their assets, it depends on the asset quality, how easily they are able to sell them. There is a possibility that units have to sell assets at discount if the assets are not liquid enough. This behavior could feed itself and turn into a depression. Thus, when the system’s liquidity decreases its fragility increases. (Minsky, 1977; Wray, 2015.)

2.2 Financial instability hypothesis and financial institutions

The Financial Instability Hypothesis (FIH) by Hyman Minsky aims to explain why financial crises occur. The theory relies on Keynes' Great Transformation, and Minsky adds a financial instability perspective to Keynes' theory. Minsky argues that a capitalist economy is going to face an economic depression from time to time. Crisis is not an exogenous event[2] but an endogenous, and financial system has to have a specific structures so that a crisis can occur (i.e. system has to be fragile). (Minsky, 1970; Minsky, 1992.)

Minsky argues that when a financial structure is stable, crises do not occur. Instability arises when a fragility of a financial structure increases. Minsky argues that this development occurs during an upswing. When an economy is booming, banks tend to increase their lending and accept loans they would not have accepted in normal times. Due to an increase in lending, firms and consumers have more money to invest. In addition, during a boom investors expect the growth to continue in the future, and as a result asset prices increase. (Minsky, 1970; Minsky, 1992.)

Minsky argues that financing is one reason why structural fragility is developed. During an upswing, profit-seeking investors are optimistic and are willing to take riskier investment opportunities. They use more external finance and a level of short-term debt increases. This action further increases the system's level of fragility. (Wray, 2015.)

As discussed in the previous chapter, Ponzi finance and speculative finance tend to increase during a boom. At the same time, government tends to increase its interest rates in order to cool down the economy. However, increase in rates lead to an increase in the payment costs of a borrower. In order to pay their debts, speculative and Ponzi finance

[2]Exogenous determinants are government and central banking arrangements. For example implementing a deposit insurance increases the stability of a financial system.

units might have to sell their assets at discount. As a result, there is a decline in asset prices which can turn into a debt-deflation process[3]. (Minsky, 1970; Minsky, 1992.)

A prolonged economic growth naturally leads to an euphoria. This development makes a financial structure more fragile as described above. In a fragile economy, crisis could be triggered by a small event, for example a decrease in cash flow, a rise in interest rate or a default of a firm or a bank. During a stable period this event would not be harmful, but if the financial structure is fragile enough it can even lead to a deep depression. (Wray, 2015.)

Minsky defines two important institutions that can help to lower a magnitude of a downturn: Big Government and Big Bank. Big Government refers to a national treasury and Big Bank to a central bank. Big Government works countercyclical: spends during a downturn and saves (e.g. collects taxes) during an upturn. These financial institutions create institutional ceilings and floors to a financial instability. For example, depositors will not withdraw their money from banks instantly when there is a run on banks if a central bank lends reserves to a bank. (Wray, 2015.)

Minsky argues that the most important job of a Big Bank is to act as a lender of last resort. The Federal Reserve (Fed) was founded after the Great Depression in 1930s to exclude the possibility of financial crises. During an downturn, Big Bank should lend reserves to troubled institutions in order to avoid defaults. After the creation of Fed it was believed that there was no possibility of a crisis. However, after 1960s America has experienced several financial crises in spite of an existence of a lender of last resort. (Minsky, 1977; Minsky, 1994.)

Even though Big Government and Big Bank decrease a system fragility they are also destabilizing. When the institutions help to resolve a crisis after a crisis they give incentives for

[3]Debt-deflation process was introduced by Irving Fisher. He argues that when economic units are forced to sell assets at discount, the assets prices decline. This process can feed itself and lead to a collapse in asset prices and to a deep depression. (Wray, 2015.)

the system to generate greater risk. After firms and banks experience that a central bank or a government will help them to recover from a crisis they start to take more risk. This development increases an instability of the system and makes a crisis more likely. (Wray, 2015.)

So, Minsky argues that even though Big Government and Big Bank are important institutions to ensure a stability of a system they are also destabilizing. Like explained before, the U.S. financial system has developed to more fragile after the World War II and Minsky claims that financial institutions, central bank and government, have helped this development. It is important to let bad firms and banks fail and that especially big banks are allowed to fail to prevent the too-big-to-fail effect. Minsky argues that perhaps the optimal way to act during a boom is to let a crisis to develop, so that dangerous firms and banks are revealed, but to act before several losses happen. (Minsky, 1970; Wray, 2015.)

2.3 Minsky's view on banking

Minsky argues that all economic units can be analyzed as banks. He views that banks do not take deposits which they then loan to people; rather, they create money as they make loans. When banks do not have enough reserves to meet cash withdrawals they turn to a central bank. A central bank lends reserves to banks so that they will not have to close. (Wray, 2015.)

Even though all economic units can be seen as banks, financial institutions are special compared to other firms. First, they operate with high leverage ratios. Second, they are protected by a government. During normal times there are no difference in normal banking and shadow banking. However, during a crisis, due to a government protection, banks are safer than shadow banks, because a lender of last resort ensures that deposits of banks are always liquid. (Wray, 2015.)

Minsky's Financial Instability Hypothesis argues that procyclicality of lending is one reason why crises occur. Minsky weights that a failure of financial intermediary affects many other units. Therefore, central banking is important for the financial system stability due to a stabilizing force. (Wray, 2015.)

Banks have several ways to reduce their risk. One is by developing bankers' skills in assessing a creditworthiness of a borrower. First, if a banker is good in assessing whether a borrower is able to pay a principal back in the future, a risk that the loan defaults decreases. Second, keeping bigger reserves and holding more liquid assets banks can reduce their risk. They are helpful in situations when a loan defaults or when a bank needs to cover withdrawals. In addition, banks can turn to a central bank, which will act as a lender of last resort, when they have troubles with cash. (Wray, 2015.)

2.4 Conclusions on Minsky's theory

In conclusion, Minsky argues that after the World War II a financial system has developed to a more and more fragile. This development has been helped by Big Government and Big Bank. In a result, the financial system has developed a structure that can turn normal market functioning into a crisis. Without a proper help from a government and a central bank, a crisis can develop to a deep depression like in 1930s in the U.S. (Wray, 2015.)

Minsky's theory explains the occurrence of crises and deep depressions by systemic fragility. He argues that during good times, when an economy is booming, a fragility develops. When governments and central banks do not let bad firms and banks fail they further increase a fragility. Even though Minsky was not alive to see the financial crisis in 2007-2008, his writings serve as a good explanation for the crisis. It has been said that the last crisis was a collapse of the whole financial system. (Wray, 2015.)

In several writings Minsky weights that stability is destabilizing. By this he means that when a government bails out firms and banks it creates incentives for them to take more risk. Even though they are stabilizing an economy by cushioning a crisis, they are destabilizing it by not letting bad firms and banks fail. After the Great Depression in 1930s there was a twenty years period when there where no crises, and which was then followed by a period of several crises. The same development can be seen after the dotcom bubble. It was believed that after the crisis, a new era has began when a possibility of a crisis was essentially zero. However, this led to the worst crisis since the Great Depression. (Wray, 2015.)

3 Prior empirical evidence

Predicting bankruptcy events is not a new thing and researchers have build different models to both estimate determinants of bankruptcies and to forecast failures. The research related to a banking divides into two classes: bank failure prediction and banking crisis prediction. In this chapter I will focus more on bank failure prediction models, but since bank failures occur mostly during banking crises (Cleary & Hebb, 2016), banking crisis prediction models are also introduced.

The two different models differ in what explanatory they use. Studies on banking crises mostly use macroeconomic factors, and bank failure studies find that bank specific factors are more important when determining the factors of bank failure probability. This is intuitive since the first model examines macro events, and the second one micro events. However, the results suggest that both bank specific and macroeconomic fundamentals should be included in the bank failure models. (Arena, 2008;Lin & Yang, 2016;Poghosyan & Čihak, 2011.)

3.1 Definition of bank failures

Previous literature use several different definitions for bank failures. Some definitions are narrower than others and focus on specific bankruptcy events, but others include also government aid and mergers. (Arena, 2008;Bongini et al., 2001;Forgione & Migliardo, 2018;Lin & Yang, 2016;Männasoo & Mayes, 2009.)

Forgione and Migliardo (2018), Kolari, Glennon, Shin, and Caputo (2002), Cleary and Hebb (2016) and Männasoo and Mayes (2009) use a narrower version of the definition. Forgione and Migliardo define a dummy that gets a value of one if the bank has been placed under receivership and gets a value of zero otherwise. Kolari et al. as well as Cleary and Hebb include only banks that were failed by Federal Deposit Insurance Corporation (FDIC). Männasoo and Mayes define bank as failed if one of the following criteria is met: (1) bankruptcy, (2) dissolved, (3) in liquidation, or (4) negative worth.

Arena (2008), Bongini et al. (2001), and Lin and Yang (2016) define a bank failure broader and add, for example, a government aid to their definition. Arena defines a bank as failed if it fits into any following categories: (1) Central bank or a government agency recapitalized the financial institution or the institution required a liquidity injection from the monetary authority, (2) the government temporarily suspended the financial institution's operations, or (3) the government closed the financial institution.

Bongini et al. (2001) use a slightly different definition than Arena (2008), and they include mergers to their definition. Lin and Yang (2016) use the same definition in their study. They define that bank is in distress if (1) the financial institution was directly closed, (2) the financial institution was merged with another financial institution, (3) the financial institution was recapitalized by either the Central Bank, the Deposit Insurance Corporation, or an agency specifically created to tackle the crisis, or (4) the financial institution's operations were temporarily suspended.

3.2 Determinants of bank failures

3.2.1 Bank specific variables

Bank specific factors used in bank failure modelling differ among studies. One reason for that might be related to a data availability. However, several studies use CAMEL variables to predict bank failures (Arena, 2008; Cole & White, 2012; Forgione & Migliardo, 2018; Poghosyan & Čihak, 2011). These variables include capitalization, asset quality, managerial quality, earnings and liquidity. Several studies find that better capitalized banks that have good earnings profiles and asset qualities are less likely to experience a bank distress (Arena, 2008; Forgione & Migliardo, 2018; Poghosyan & Čihak, 2011).

Forgione and Migliardo (2018) study Italian banks between 2007 and 2012. They use logit regression to determine which factors affect a probability of a bank distress and use it to forecast bank distress in 2013 and 2014. They find that asset quality, impaired loans, management competence, and loan to deposit ratios are important when determining bank distress. Especially the equity ratio is significant and implies that better capitalized banks are less likely to be failed. Furthermore, the results suggest that the asset quality has a non-linear effect, and that non-performing loans, earnings, and size have no effect on the likelihood of a bank distress.

Poghosyan and Čihak (2011) use data on European banks and study which factors affect bank soundness between 1996 and 2007. Like Forgione and Migliardo (2018), they find that better capitalized banks are less likely to experience a bank distress. Furthermore, earnings is negatively correlated with the probability, but managerial quality and liquidity do not have any impact. In addition, their results suggest that contagion effect is important when forecasting bank distress, and that more concentrated banking systems are more likely to experience a bank distress. The latter finding is in line with the concentration-fragility view and will be discussed later in the next chapter.

Männasoo and Mayes (2009) focus on Eastern European countries and study whether macroeconomic, bank specific and structural factors can explain bank distress. They find that all the aspects are important. The results suggest that macroeconomic factors are important when determining the timing of a bank distress, whereas bank specific variables are important when determining which banks are most likely to experience a distress. Unlike Poghosyan and Čihak (2011), Männasoo and Mayes find that liquidity is important early warning indicator. Furthermore, they find that both equity to assets and cost to income ratio have negative coefficients, but their effect on a likelihood of a bank failure is not highly significant. Lastly, earnings, loans to assets ratio, and efficiency do not affect a probability of a bank distress in Eastern European countries.

Arena (2008) examines banking crises in East Asia and Latin America, and also finds that bank specific variables are important when determining distressed banks. He finds that banks that have better asset quality and solvency rates, better liquidity, and which are more profitable are less likely to be failed. In Latin America the ratio of loan loss provision to total loans is positive and significant, but in East Asia it does not significantly affect a probability of a bank failure. In addition, Arena finds that bigger banks and foreign owned banks are less likely to be failed.

Like Arena (2008), also Lin and Yang (2016) study East Asian countries. However, unlike Arena, they use data from 1999 to 2010 that covers the financial crisis of 2007-2009. Their results are similar as Arena's; they find that capital adequacy, asset quality, management quality, profitability, and liquidity have a significant effect on a probability of a bank failure. In addition, like Männasoo and Mayes (2009), Lin and Yang argue that bank fundamentals are more important than macroeconomic fundamentals when determining bank failure, whereas macroeconomic factors are more crucial in bank survival time analysis.

Cleary and Hebb (2016) and Cole and White (2012) examine U.S. banks during the last financial crisis. Cole and White include CAMEL variables into their model and find that all of them are important determinants of bank failures. The results are consistent with the results from 1985-1992 banking crisis. Cleary and Hebb find that capitalization, loan quality, and profitability are important factors of bank failures.

Because bank failures mostly occur during crisis periods, it is justifiable to discuss also about studies that predict banking crises. Most research papers on banking crises focus on macroeconomic variables (Demirgüç-Kunt & Detragiache, 1998, 2005), but some take account also for bank specific factors (Demirgüç-Kunt & Detragiache, 1998, 2005). Moreover, Demirgüç-Kunt and Detragiache (1998) and Demirgüç-Kunt and Detragiache (2005) find that excessive credit growth increases a probability of a banking crisis.

The research papers above study bank failures and banking crises all over the world. From the results it can be concluded that bank specific factors are important when determining a probability of a bank failure. Furthermore, CAMEL factors, especially asset quality, are found to have a significant effect on a probability of a bank failure.

3.2.2 Macroeconomic variables

Even though, Männasoo and Mayes's (2009) and Lin and Yang (2016) argue that bank specific factors are more important than macroeconomic factors when determining bank failures, several studies find that macroeconomic variables contain important information about a likelihood of a bank failure (Čihák & Schaeck, 2010; Lin & Yang, 2016; Männasoo & Mayes, 2009; Poghosyan & Čihak, 2011). Thus, they should be included in forecasting models.

Männasoo and Mayes (2009) and Lin and Yang (2016) find that inflation and interest rate affect a probability of a banking crisis. Both factors have positive coefficients which implies that a higher inflation and a higher interest rate increase a probability of a bank failure. In addition, Männasoo's and Mayes' results suggest that a higher ratio of private lending to GDP is associated with a higher probability of a bank failure, and Lin's and Yang's results that a higher GDP growth, foreign reserves and exports level results a higher likelihood of a failure.

Contrast to studies above, Čihák and Schaeck (2010) find that GDP growth and inflation do not significantly affect a probability of a bank failure, whereas M2 to international reserves and GDP per capita are significant determinants. The results suggest that an increase in a level of economic development and a decrease in the ratio of M2 to foreign reserves results a decrease in a probability of a bank failure.

Boyd and De Nicolo (2005) examine how competition and concentration affect bank's risk taking incentives. They find support for the concentration-fragility view, which means that when a banking system becomes more concentrated the fragility increases. Also Poghosyan and Čihak's (2011) results support the view. Their results suggest that increase in banking system's concentration leads to an increase in a likelihood of a bank failure. In addition, they find that contagion effect is important among EU banks.

Banking crises studies' results are similar to bank failure studies'. Demirgüç-Kunt and

Detragiache (1998) argue that GDP growth, interest rate, inflation and M2 to foreign reserves have a significant impact on a probability of a banking crisis. The results are similar as in bank failure studies. Later, the authors update their analysis and get the same results as previously. However, they add a ratio of private credit to GDP which is found to be positive and statistically significant. It means that if the GDP does not change, an increase in private credit leads to an increase in the probability of a banking crisis.

In conclusion, based on previous literature macroeconomic factors are valuable add to a model for determining the determinants of bank failures. For example, Arena (2008) argues that bank specific factors are not enough to explain the differences between different countries' probabilities of bank failures, but banking system and macroeconomic factors hold important information for that. As it can be hypothesized, banks that operate in a more favourable economic environment (i.e. higher GDP growth, lower inflation and interest rate) have better likelihood to survive than banks that operate in a worse economic environment.

Overall, based on prior empirical results, it is clear that many different factors are connected to a probability that bank fails. Researchers have used dozens of different factors and many of them are found to have a significant effect on bank failure probability. However, adding more variables to a model does not necessarily mean that the model is better. Thus, factors should be chosen carefully based on previous research, data availability, and most importantly data analysis.

3.3 Forecasting methods

Researchers have examined bankruptcies since the 1930s and used several different models and methods ranging from univariate analysis to models that use complex mathematical and algorithmic elements. The first study that used multivariate analysis was done by Altman (1968). Since then, authors have used several other methods in order to predict firm and bank failures. The most popular ones are discriminant analysis (DA), logit and probit models, and neural network method. In this chapter I will focus on these models and discuss their use and predictive accuracies. (Bellovary, Giacomino, & Akers, 2007.)

Altman (1968) was the first one to use the DA approach. In DA the data is divided into two groups: bankruptcy or non-bankruptcy. Then a linear function is build from the factors which are possible determinants of bankruptcies. Lastly, differences between the groups in terms of factor coefficients are analysed to make conclusions. Bellovary et al. (2007) paper reviews several different prediction methods, and they conclude that discriminant analysis has the highest model accuracy in addition to a neural network analysis. However, the DA has some disadvantages; it requires normal distribution of the variables and uses cross-sectional data.

Altman (1968) and Cleary and Hebb (2016) use Z-score to predict bankruptcies. Altman studies firm bankruptcies, and Cleary's and Hebb's bank failures. Altman's model is able to predict 94 % of the bankruptcies correctly, and the model predicts accurately up to two years prior the event and after that it diminishes rapidly. Cleary and Hebb model is able to predict as well as Altman's; the model's out-of-sample accuracy ranges from 90 % to 95 %.

Logit and probit models use a probability of a bank failure as a dependent variable. Models are the same otherwise but probit model requires a non-linear estimation (Bellovary et al., 2007). Even though, based on Bellovary et al. (2007), the models do not outperform discriminant analysis and neural network in terms of predictive accuracy, they have been used widely in bank failure prediction (Arena, 2008; Bell, 1997; Čihák & Schaeck, 2010; Davis & Karim, 2008; Lin & Yang, 2016; Poghosyan & Čihak, 2011). In addition, Lo (1986) compares logistic regression and DA, and he's results suggest that the models might be equally good.

For example, Bell (1997) and Davis and Karim (2008) use logistic model to study determinants of bank failures. Bell (1997) compares neural network and logit methods. He finds that neither model dominates, but neural network might be better in situations where decision process is complex (e.g. in nonlinear decision processes). Davis and Karim (2008) find that multinominial logit model might be better for predicting bank failures in a global context, whereas a signal extraction may be better in a country-specific forecasting.

Neural network analysis is a more complex method, and it appeared the first time in research papers in the late 1980s (Bellovary et al., 2007). Neural network is composed of different layers, nodes, connections and connection weights, and has gotten inspiration from the human nervous system. The network transforms data by using different transform functions to get an output that is close to a target value and uses an iterative learning process to improve its performance through the process. Neural network's advantages are that it does not assume any specific statistical distribution, and that is uses nonlinear approach. (Bell, 1997;Demyanyk & Hasan, 2010.)

Several studies find that neural networks outperforms other forecasting models (Bellovary et al., 2007; Jo, Han, & Lee, 1997). However, based on Davis and Karim's (2008) and Bell's (1997) results, it might actually depend on the situation which model is the best on in terms of predictive accuracy. In addition, neural network method is much more complex than, for example, discriminant analysis or logit regression.

In addition to methods described above, researchers have developed models that combine two or more different methods. Canbas, Cabuk, and Kilic (2005) combines principal component analysis (PCA), discriminant analysis and probit and logit models into one integrated early warning system (IEWS). The results show that the IEWS can accurately predict bank failures.

Olmeda and Fernández (1997) compare statistical techniques which use one method and those that use two or more different methods. When they compare five single models, they find that neural network is the most accurate one. Logit model is the second most accurate and DA is the least accurate. Lastly, the authors compare a performance of single models to the performance of combined models. The results suggest that the optimal model combines at least two different statistical models.

In conclusion, in previous literature authors have used several different prediction models. The most popular ones are DA, logit and probit models, and neural network. From those methods, the neural network approach has the highest prediction accuracy based on previous results (Bellovary et al., 2007; Jo et al., 1997; Olmeda & Fernández, 1997). However, Olmeda and Fernández (1997) points out that computing neural network calculations is significantly slower than, for example, computing logit regression. Lastly, Bellovary et al.'s (2007) review suggest that in addition to neural network, discriminant analysis performs well when predicting bankruptcies.

3.4 Predictive accuracy

Previous studies have used both in-sample and out-of-sample analysis to assess a predictive accuracy of forecasting models. Several studies have included an out-of-sample analysis since it is a valid way to assess a predictive power of a model. The most used method to analyse models is to use Type I and Type II errors. Type I error occurs when a model misclassifies failed bank as non-failed bank, and Type II when a model misclassifies non-failed bank as failed bank. To receive higher accuracy, the errors should be minimized.

In logit analysis the Type I and Type II errors can be affected by modifying a cutoff value which determines which banks are treated as healthy and which as failed. Decreasing the cutoff value increases the Type II error, and increasing the value increases the Type I error. The optimal cutoff point depends on how these two errors are weighted. Bellovary et al. (2007) and Poghosyan and Čihak (2011) argue that Type I error is more important than Type II since it can be more costly for policymakers to determine banks as healthy even though they are in trouble.

Poghosyan and Čihak (2011) use logit model, and discuss about different cutoff points, as well as analyse the results by changing the point. With 10 % cutoff value the model classifies 55.7 % of the distressed events correctly. Decreasing the value to 1 % increases the per cent to 63 %, but also increases the misclassification of healthy banks as distressed.

Also Forgione and Migliardo (2018) use a logit analysis, and their model's predictive power is significantly better than Poghosyan and Čihak's (2011). The model can predict failed banks correctly 96.7 % of the time, and it misclassifies healthy banks as failed 20-26.77 % of the time. The high predictive accuracy results from using in-sample. In contrast, when the data is extracted to all euro area banks, Italian banks excluded, the model's accuracy drops to 64 % and Type II error increases to 36-39 %.

Bell (1997) gets relatively high predictive accuracy level by using logit analysis for out-of-sample analysis. Like Poghosyan and Čihak (2011), they try different cutoff points, and with 1 % value the model predicts 99 % of the failed banks correctly, and with 10 % it predicts 90 % correctly. Even if the value is increased to 80 % the accuracy is 52 %, which is almost the same as Poghosyan and Čihak's (2011) result with 10 % cutoff point. Also Bell uses neural network modeling and the predictive accuracy with that method is as high as with the logit model.

Cleary and Hebb (2016) use discriminant analysis to predict U.S. bank failures between 2002 and 2009. Their model can predict successfully failed banks in both in-sample and out-of-sample. In-sample analysis predicts 92 % of the failed banks correctly, and out-of-sample predicts 90-95 % correctly. They use both annual data and quarterly data and find that using quarterly data the predictive accuracy increases significantly.

Olmeda and Fernández (1997) compare several different models and even though they find that neural networks is more accurately than other single models, the results by Bell (1997), Cleary and Hebb (2016) and Forgione and Migliardo (2018), which use logit model, are significantly better. Olmeda's and Fernandez's results suggest that combining several different methods results the best prediction accuracy which is 81.81 % for American banks in out-of-sample. In contrast, the same results for discriminant analysis, logit model and neural networks are 72.72 %, 78.18 %, and 80.00 % respectively.

Table 1 lists the studies represented above and summarizes how well the models are able to predict bank failures. The predictive power of the forecasting models ranges from 52 % to 99 %. As can be expected, the results for in-sample analysis are better than for out-of-sample analysis (Forgione & Migliardo, 2018). Even though in the previous chapter it is discussed that neural networks and discriminant analysis are the most suitable models for forecasting bankruptcies, the results from the bank failure prediction models suggest that logistic regression's predictive accuracy is as high as Discriminant Analysis'.

Table 1. Summary of predictive powers of the models used in previous studies.

Study	Model	In-sample	Out-of-sample
Poghosyan and Čihak (2011)	logit model	55.7 - 63 %	-
Forgione and Migliardo (2018)	logit model	96.7 %	64 %
Bell (1997)	logit model[1]	52 % - 99 %	-
Cleary and Hebb (2016)	Discriminant Analysis	92 %	90 - 95 %

[1] Bell (1997) examines also neural network method and get similar results as for logit model.

4 Methodology

In this section I explain statistical methods that I use in my empirical analysis. First, I discuss how H-statistics, which is a measurement of bank competition, is estimated. Lastly, I introduce a logistic model which is the primary empirical method of my analysis.

4.1 H-statistic

I use Panzar & Rosse H-statistic as an approximation of a bank competition. For example, Schaeck, Cihak, and Wolfe (2009) and Claessens and Laeven (2003) use this approach in their studies, and I follow their analysis. H-statistic determines whether a banking system has a monopoly, a perfect competition, or a monopolistic competition[4]. If H-statistic is smaller than 1, it indicates a monopoly. If H-statistic is equal to 1, it indicates a perfect competition, and if H-statistic is between 0 and 1, it indicates monopolistic competition.

I estimate the same revenue equation as Schaeck et al. (2009) and Claessens and Laeven (2003). The equation is estimated separately for each country.

$$\log \mathrm{P}_{\mathrm{it}} = \alpha + \beta_1 \log \mathrm{W}_{1,\mathrm{it}} + \beta_2 \log \mathrm{W}_{2,\mathrm{it}} + \beta_3 \log \mathrm{W}_{3,\mathrm{it}} + \gamma_1 \log \mathrm{Y}_{1,\mathrm{it}} + \gamma_2 \log \mathrm{Y}_{2,\mathrm{it}} + \gamma_3 \log \mathrm{Y}_{3,\mathrm{it}} + \delta \mathrm{D} + \epsilon_{\mathrm{it}}, \tag{1}$$

where P_{it} is a ratio of gross revenue to total assets, $\mathrm{W}_{1,\mathrm{it}}$ is a proxy for input price of deposits (ratio of interest expenses to total deposits and money market funding), $\mathrm{W}_{2,\mathrm{it}}$ is a proxy for input price of labor (ratio of personnel expenses to total assets), $\mathrm{W}_{3,\mathrm{it}}$ is a proxy for input price of equipment/fixed capital (ratio of other operating and administrative expense to total assets. Furthermore, i refers to a bank i and t to a year t.

[4]Monopoly refers to a system where one firm dominates a market. Under perfect competition there are several firms that offer their products and services. In a monopolistic competition there are several different firms which offer products and services which are not perfect substitutes even though they are similar. (Begg, Fiscer, & Dornbusch, 2005, p. 143.)

I include the same control variables as Schaeck et al. (2009) and Claessens and Laeven (2003): $Y_{1,it}$ is a ratio of equity to total assets, $Y_{2,it}$ is a ratio of net loans to total assets, $Y_{3,it}$ is a total assets and D is a vector of year dummies. All variables are in logarithmic form. The model is estimated by using a panel regression with fixed effects. The H-statistic is then calculated as following: $\beta_1 + \beta_2 + \beta_3$.

4.2 Logit model

I use logistic regression model in my analysis because the method has been widely used in bank failure prediction and previous research shows it performs well (Bell, 1997; Forgione & Migliardo, 2018; Olmeda & Fernández, 1997; Poghosyan & Čihak, 2011). Logit model is an appropriate method when a dependent variable is binary. In this case a bank is either failed or not failed. The model predicts an impact of different factors on a probability of a bank failure.

Logistic model can be represented as a log odds ratio. A dependent variable, log odds ratio, is a ratio of a probability of a bank failure to a probability of a no bank failure. The odds ratio is a function of K explanatory variables. The model is shown below.

$$\log \frac{P_{it}}{1 - P_{it}} = \beta_0 + \sum_{k=1}^{K} \beta_k X_{k,it} + \epsilon_{it}, \tag{2}$$

where P_{it} is a probability that bank i is failed at time t. $X_{k,it}$ is k^{th} explanatory variable of a bank i at time t, and β measures the impact of the explanatory variable on the log odds ratio. Thus, if the slope coefficient is negative (positive), change in the independent variable results a decrease (increase) in the likelihood of a bank failure. The explanatory variables used in this research are listed in Table 2.

When estimating logistic regression, the appropriate cutoff value must be chosen. Type I and Type II errors depend on the cutoff value, and the most appropriate model minimizes these errors. Cutoff value determines which banks are treated as failed and which as healthy. If the value is low, Type II error is high, and if the value is high, Type I error is high. The optimal value depends on how these errors are weighted. Since it can be expensive to miss failed banks, Bellovary et al. (2007) and Poghosyan and Čihak (2011) argue that Type I error should be weighted more than Type II error.

As explained previously, I have k number of explanatory variables X. My main research hypothesis is as following:

H_0: Variable X does not affect a probability of a bank failure
H_1: Variable X affects a probability of a bank failure

My independent factors are listed in Table 2. They are logarithmic total assets (*lg_assets*), equity to assets ratio (*eq_a*), cir, ROA, liquid assets to total assets ratio (*liqa_a*), total loans to customer deposits ratio (*loan_custdeps*), loan loss provision to total loans ratio (*llprov_loan*), GDP growth (*gdp_growth*), GDP per capita growth (*gdp_pc_gr*), inflation, domestic credit to GDP (*credit_gdp*), interest rate (*int_rate*), HHI and h-statistic (*h_stat*). Table A1 lists the main studies of my paper and which variables they have found to be significant or insignificant.

The research hypotheses for a size are

H_0: Size does not affect a probability of a bank failure
H_1: Size affects a probability of a bank failure

Based on previous research I expect that size has a negative effect on a probability of a bank failure (Arena, 2008). More specifically, increase in a size decreases a likelihood of a bank failure. The hypothesis supports the ”too-big-to-fail” hypothesis.

The research hypotheses for a capitalization are

H_0: Capitalization does not affect a probability of a bank failure

H_1: Capitalization affects a probability of a bank failure

In most of the previous research, capitalization is found to be a significant factor of bank failures. So, I expect that it has a significant effect on a bank failure probability, and based on previous research I expect that a higher capitalization implies a lower probability of a bank failure. (Arena, 2008; Poghosyan & Čihak, 2011; Lin & Yang, 2016.)

The research hypotheses for a managerial quality are

H_0: Managerial quality does not affect a probability of a bank failure
H_1: Managerial quality affects a probability of a bank failure

As Table A1 shows, managerial quality is in most studies insignificant. Even though I do not expect it to have a significant effect on a bank failure probability, my hypothesis is that increase in cost to income ratio (decrease in managerial quality) increases a probability of a failure as Lin and Yang's (2016) results suggest.

The research hypotheses for earnings are

H_0: Earnings does not affect a probability of a bank failure
H_1: Earnings affects a probability of a bank failure

I expect that earnings will have a significant effect on a probability of a failure, and that an increase in earnings decreases a probability. The hypothesis is supported by previous research by Arena (2008), Čihák and Schaeck (2010), Lin and Yang (2016), and Poghosyan and Čihak (2011).

The research hypotheses for liquidity ratios are

H_0: Liquid assets to total assets does not affect a probability of a bank failure
H_1: Liquid assets to total assets affects a probability of a bank failure

AND

H_0: Total loan to total customer deposits does not affect a probability of a bank failure

H_1: Total loan to total customer deposits affects a probability of a bank failure

Based on previous research, I expect that increase in liquid assets to total assets and decrease in total loans to total customer deposits increases a likelihood of a bank failure. Both factors are found to be significant in most of the research papers. Thus, I expect the same. (Arena, 2008; Forgione & Migliardo, 2018; Lin & Yang, 2016.)

The research hypotheses for an asset quality are

H_0: Asset quality does not affect a probability of a bank failure

H_1: Asset quality affects a probability of a bank failure

Arena (2008) finds that loan loss provision to total loans does not have a significant effect on bank failure probability but Poghosyan and Čihak (2011) find the contrary. Since Poghosyan and Čihak study European banks and the data is more recent than Arena's data, my hypothesis is that the ratio has a significant effect on a bank failure likelihood. Furthermore, I expect that an increase in the ratio (decrease in asset quality) increases a likelihood of a failure (Arena, 2008; Poghosyan & Čihak, 2011).

The research hypotheses for a GDP growth are

H_0: GDP growth does not affect a probability of a bank failure

H_1: GDP growth affects a probability of a bank failure

Expectations for macroeconomic factors are intuitive and imply that better economic environment decreases a probability of a bank failure. Thus, my hypothesis is that GDP growth has a negative relationship with a bank failure probability. Since macroeconomic factors and bank failures are not as well researched as bank specific factors and bank failures, it is hard to make clear expectations about the significance of the variables. However, since two out of three studies find that GDP growth is insignificant, I expect to find similar results. (Arena, 2008; Demirgüç-Kunt & Detragiache, 2005; Lin & Yang, 2016.)

The research hypotheses for a GDP per capita growth are

H_0: GDP per capita growth does not affect a probability of a bank failure
H_1: GDP per capita growth affects a probability of a bank failure

As GDP growth, I expect that GDP per capita growth and a bank failure probability have a negative relationship. Moreover, increase in GDP per capita growth decreases a probability of a bank failure (Arena, 2008). Since Arena (2008) finds that the variable is significant, also I expect that GDP per capita growth has a singificant effect on a probability of a bank failure.

The research hypotheses for an inflation are

H_0: Inflation does not affect a probability of a bank failure
H_1: Inflation affects a probability of a bank failure

Since previous research has found that inflation tend to be significant and positively correlated with a likelihood of a bank failure, I expect that increase in inflation significantly increases a bank failure probability (Demirgüç-Kunt & Detragiache, 2005; Lin & Yang, 2016).

The research hypotheses for an interest rate are

H_0: Interest rate does not affect a probability of a bank failure
H_1: Interest rate affects a probability of a bank failure

Hyman Minsky predicts that interest rate tends to increase before a banking crises (Minsky, 1992, 1994). Based on his prediction and results from previous research papers, I expect that interest rate and a bank failure likelihood have a positive and significant relationship (Arena, 2008; Lin & Yang, 2016; Männasoo & Mayes, 2009).

The research hypotheses for a domestic credit to GDP are

H_0: Domestic credit to GDP does not affect a probability of a bank failure
H_1: Domestic credit to GDP affects a probability of a bank failure

In addition to interest rate, Minsky predicts that banks tend to increase their lending during a boom (Minsky, 1970, 1992). Thus, I expect that increase in the ratio increases a bank failure probability. However, Čihák and Schaeck (2010) results suggest that the effect is not significant which is why I expect similar results.

The research hypotheses for a concentration are

H_0: Concentration does not affect a probability of a bank failure
H_1: Concentration affects a probability of a bank failure

Results from previous research suggest that more concentrated banking systems tend to be less stable. Thus, my hypothesis is that a higher concentration implies a higher probability of a bank failure, and that the effect is significant. (Poghosyan & Čihak, 2011.)

The research hypotheses for a competition are

H_0: Competition does not affect a probability of a bank failure
H_1: Competition affects a probability of a bank failure

Consistent with the hypothesis for concentration, I expect that competition is negatively related to a bank failure probability. More specifically, banks that are operating in a banking system that has a higher competition, are less likely to be failed. (Boyd & De Nicolo, 2005.)

5 Data

In this chapter I present my data. I introduce my dependent and my independent variables, and examine them deeper by presenting some descriptive statistics. In my analysis I use commercial banks from EU-12 countries before and during the financial crisis of 2007-2008. The EU-12 countries are Austria, Belgium, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain and United Kingdom.

5.1 Dependent variable

I define a bank failure as in the paper by Bongini et al. (2001), which means that I will include banks that were closed, merged with another financial institution[5], recapitalized, or banks which operations were temporarily suspended. I create a dummy variable that is equal to 1 when the bank is failed and 0 when it is not. Because in some cases one bank has received state aid more than once, some banks are defined as failed more than once.

I am going to use data provided by Open Economics Working Group and European Commission. Open Economics Working Group is association at the University of Cambridge and its membership consists of leading academics and researchers and other experts around the world. Since there is a gap in the information of bank failures in Europe, the group has created a list of European bank failures. European Commission provides information about state aids that has been provided to European banks as well as bank mergers.

In total I have 1,674 banks from which 69 are failed during a time period from 2006 to 2012. Figure 1 presents how the failures are distributed in the time period. From the figure it can be seen that a peek in the number of failures occurs in 2008. Before that there was only one bank failure in 2006. Between 2009-2012 the frequency of failures

[5] I have included only cases when a merger was due to problems in other party's operations, i.e. a bank would have gone bankruptcy without a merger.

is between 9 and 12. These results are consistent with the finding that bank failures tend to occur during a crisis periods (Cleary & Hebb, 2016).

Table A2 represents the number of bank failures by year and country. There are three countries that have significantly more bank failures than others: Greece, UK, and Spain. There are 13 bank failures in Greece, 16 in UK, and 10 in Spain. In other countries the number of failures ranges from 1 to 6.

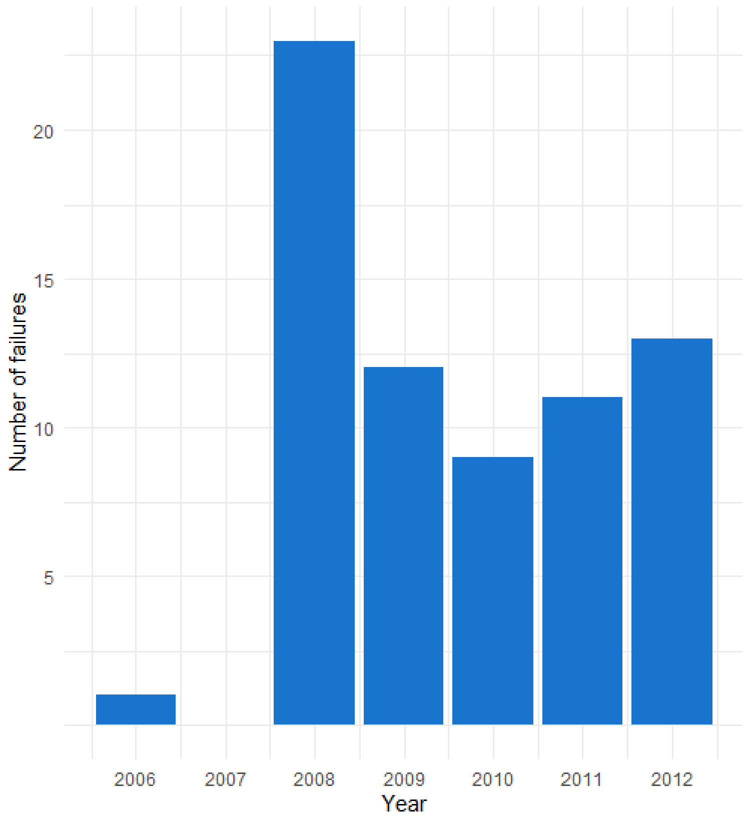

Figure 1. Number of bank failures by year from 2006 to 2012.

5.2 Independent variables

Several studies have found that CAMEL variables can predict well bank failures which is why I include them into my model (Arena, 2008; Forgione & Migliardo, 2018; Lin & Yang, 2016; Poghosyan & Čihak, 2011). As Lin and Yang (2016), Poghosyan and Čihak (2011), Arena (2008), Cleary and Hebb (2016), Forgione and Migliardo (2018) and Männasoo and Mayes (2009), I proxy capitalization by a ratio of equity to total assets, earnings by return on assets (ROA), and managerial quality by cost to income ratio. For liquidity and asset quality there are several different proxies. Based on my data availability, I use a ratio of liquid assets to total assets like Poghosyan and Čihak (2011), and a ratio of total loans to customer deposits like Forgione and Migliardo (2018) as a proxies for liquidity. A ratio of loan loss provisions to total loans is used as a proxy for asset quality. Both Poghosyan and Čihak (2011) and Arena (2008) have used that variable.

Because macroeconomic information can increase a predictive power of a model, I include several factors that proxy for example economic development and concentration of the banking system. Previous studies find that GDP growth, GDP per capita growth, inflation, interest rate, domestic credit to GDP, and concentration are correlated with a probability of bank failures (Čihák & Schaeck, 2010; Demirgüç-Kunt & Detragiache, 2005; Lin & Yang, 2016; Poghosyan & Čihak, 2011).

I include variables that are listed above to my model. I use short-term interest rate to proxy monetary policy. Concentration is proxied by Herfindahl-Hirschman index which is a sum of squared market shares (total assets). This proxy has been used by Poghosyan and Čihak (2011) and Männasoo and Mayes (2009). In addition, I calculate Panzar & Rosse H-statistic which measures a competition in the banking system. Competition and bank failures have not been studied before, in my knowledge, but it has been used in banking stability studies (Schaeck et al., 2009). All of the explanatory variables and their anticipated signs are listed in Table 2.

Based on the previous research, size, capitalization, earnings, and liquidity are negatively related to a probability of a bank failure (Arena, 2008; Čihák & Schaeck, 2010; Lin & Yang, 2016; Poghosyan & Čihak, 2011). This means that bigger banks are less likely to be failed which is consistent with the ”too-big-to-fail” hypothesis. Furthermore, better capitalized banks that have higher earnings and liquidity have a lower probability of a bank failure. Cost to income ratio, total loans to total customer deposits and loan loss provisions to total loans are found to be positively related to a bank failure probability (Forgione &

Migliardo, 2018; Lin & Yang, 2016; Männasoo & Mayes, 2009; Poghosyan & Čihak, 2011). Thus, higher cost to income (lower managerial quality) and loan loss provisions to total loans (lower asset quality) increases a probability of a bank failure. Lastly, Forgione and Migliardo (2018) find that Italian banks tend to have too high loan to deposits ratio which makes banks less stable.

In addition, previous research finds that banks that operate in a better economic environment are less likely to be failed which is intuitive. More specifically, increase in GDP growth and GDP per capita growth and decrease in inflation decreases a probability of a bank failure. Domestic credit to GDP ratio and interest rate are expected to be positively related to a bank failure probability since the theory of bank failures by Hyman Minsky predicts that domestic credit and interest rate tends to increase before a crisis. Lastly, Poghosyan and Čihak (2011) and Boyd and De Nicolo (2005) find that higher concentration and lower competition increase a probability of a bank failure.

Table 2. Explanatory variables.

Variable	Anticipated sign	Explanation
Total assets	-	Size
Equity/Assets	-	Capitalization
Cir	+	Cost to income ratio, managerial quality
ROA	-	Return on Assets, earnings
Liq. assets/assets	-	Liquidity
Loan/Cust. dep.	+	Total loans to customer deposits, liquidity
Llprov/Loans	+	Loan loss provisions to total loans, asset quality
GDP growth	-	Real GDP growth
GDP per capita growth	-	Economic development
Inflation	+	Inflation rate
Domestic credit/GDP	+	Amount of credit compared to GDP
Interest rate	+	Short-term interest rate, monetary policy
HHI	+	Herfindahl-Hirschman index, concentration of a banking system
H-statistic	-	Panzar-Rosse H-statistic, competition

5.3 Descriptive statistics

Next I describe my data in more details. The bank data has been collected from Fitch Connect, and the macroeconomic data from the World Bank's database. Table 3 and Table 4 present correlation tables for bank specific variables and macroeconomic variables, respectively. Based on the results there are no large correlations between any bank-specific variables. Table 4 reveals that GDP growth (*gdp_growth*) and GDP per capita growth (*gdp_pc_gr*) are highly correlated as can be expected. Also concentration (*HHI*) and competition (*h_stat*) have high correlation (-0.57) but that is not too high to create a problem with multicollinearity[6]. However, because the correlation is quite high, the variables are studied both separately as well as together.

Table 3. Correlation table: bank-specific variables.

	lg_assets	eq_a	cir	ROA	llprov_loan	liqa_a	loan_custdeps
lg_assets	1.00						
eq_a	-0.31	1.00					
cir	-0.15	-0.11	1.00				
ROA	-0.09	0.40	-0.39	1.00			
llprov_loan	-0.02	-0.04	-0.11	-0.14	1.00		
liqa_a	0.02	0.12	0.02	0.10	-0.02	1.00	
loan_custdeps	0.06	0.06	-0.12	0.13	0.04	-0.08	1.00

Table 4. Correlation table: macroeconomic variables.

	gdp_growth	gdp_pc_gr	inflation	int_rate	HHI	h_statistic	credit_gdp
gdp_growth	1.00						
gdp_pc_gr	0.97	1.00					
inflation	0.33	0.27	1.00				
int_rate	-0.06	-0.11	0.24	1.00			
HHI	-0.07	-0.16	0.26	0.11	1.00		
h_statistic	0.15	0.22	-0.12	0.03	-0.57	1.00	
credit_gdp	-0.08	-0.12	0.14	-0.38	0.40	-0.20	1.00

Table 5 presents descriptive statistics for the bank specific variables for the whole sample and two subsamples: not failed banks and failed banks. I have excluded extreme values that are under the 1st percentile and over the 99th percentile. The table represents the descriptive statistics for seven different bank-specific factors. *Lg_assets* stands for logarithm of total assets, *cir* for cost to income ratio, *ROA* for return for assets, *eq_a* for equity to total assets ratio, *liqa_a* for liquid assets to total assets ratio, *llprov_loan* for loan loss provisions to total loans ratio, and *loan_custdeps* for total loans to total customer deposits ratio.

The results in Panel B clearly state that there is a difference between the two groups. Based on the results, failed banks tend to be larger which contradicts the ”too-big-to-fail” hypothesis and my expectations. Furthermore, failed banks tend to have larger cost

[6] (Kennedy, 2003, p. 209) shows that multicollinearity creates a problem when the correlation is about 0.8 or 0.9 in absolute value

to income and loan loss provisions ratios. This means that failed banks have worse managerial quality and asset quality than not failed banks. In addition, they tend to have lower level of liquidity, earnings, and capitalization. Results of univariate tests that are presented in Table 6 show that all of the differences are statistically significant except loan_custdeps.

Table 5. Descriptive statistics: Bank specific variables.

Panel A: Total sample

	N	mean	sd	min	max
lg_assets	10937	3.11	0.86	1.53	5.97
cir	10985	66.31	14.38	18.68	146.01
ROA	10797	0.43	0.58	-2.80	4.17
eq_a	11034	8.20	4.82	1.34	48.91
liqa_a	10704	16.45	14.37	0.10	85.66
llprov_loan	10472	0.59	0.77	-2.81	4.70
loan_custdeps	10869	241.27	989.27	6.33	15057.58

Panel B: Failed banks and not failed banks

	Failed banks					Not failed banks				
	N	mean[1]	sd	min	max	N	mean	sd	min	max
lg_assets	60	4.44	0.90	1.78	5.88	10877	3.11	0.85	1.53	5.97
cir	58	74.37	19.44	29.91	136.15	10927	66.27	14.34	18.68	146.01
ROA	43	-0.36	0.85	-2.08	1.34	10754	0.43	0.58	-2.80	4.17
eq_a	47	4.63	3.26	1.42	19.04	10987	8.21	4.82	1.34	48.91
liqa_a	61	12.54	11.45	1.61	54.03	10643	16.47	14.38	0.10	85.66
llprov_loan	46	1.21	1.19	0.00	4.47	10426	0.58	0.76	-2.81	4.70
loan_custdeps	44	251.75	750.90	56.31	5111.03	10825	241.23	990.14	6.33	15057.58

Note: All of the variables are in percentage form.
[1]The mean is calculated as an average over time for both subsamples.

Table 6. Univariate tests for bank specific variables.

	Mean				
	failed	not failed	difference	t-stat	p-value
lg_assets	4.44	3.11	1.33	11.46	0.000
cir	74.37	66.27	8.10	3.17	0.002
ROA	-0.36	0.43	-0.79	-6.13	0.000
eq_a	4.63	8.21	-3.58	-7.51	0.000
liqa_a	12.54	16.47	-3.93	-2.67	0.010
llprov_loan	1.21	0.58	0.63	3.59	0.001
loan_custdeps	251.75	241.23	10.52	0.09	0.927

Table 7 represents the same descriptive statistics for macroeconomic variables as Table 5 for bank specific. *Gdp_growth* stands for GDP growth, *gdp_pc_gr* for GDP per capita growth, *int_rate* for interest rate, *HHI* for concentration, *h_stat* for competition, and *credit_gdp* for Domestic credit to GDP ratio.

Table 7. Descriptive statistics: Macroeconomic variables.

	N	mean	sd	min	max
gdp_growth	11718	0.97	2.95	-9.13	8.36
gdp_pc_gr	11718	0.82	3.14	-9.00	6.69
inflation	11718	1.97	0.93	-4.48	4.90
int_rate	11718	2.34	1.40	0.61	5.66
HHI	11718	1156.49	579.42	693.55	3719.92
h_stat	11718	0.39	0.11	-0.18	0.87
credit_gdp	11718	149.51	30.20	106.49	250.50

6 Empirical analysis

In this chapter I present the results of my empirical analysis. I start by examining which factors are determinants of bank failures and how they affect a probability of a failure. Next, I study deeper how bank specific variables behave before a bank failure. Lastly, I use my model to predict bank failures in out-of-sample and examine whether a number of predicted bank failures has decreased after 2012.

6.1 Determinants of bank failures

In this chapter my aim is to find determinants that the best explain bank failures. I include both bank specific and macroeconomic factors and all of the factors are lagged by first lags. Because HHI and H-statistic have a high correlation, I first study them separately. In Table 8, Models 1 and 2 use HHI and Models 3 and 4 use H-statistic. Furthermore, Models 1 and 3 include time fixed effects whereas Models 2 and 4 include both time fixed effects and country fixed effects[7]. I do not include any bank fixed effects because my dependent variable is defined so that one bank might be failed more than once[8].

Table 8 introduces regression results for my baseline models. Size is found to be a highly significant determinant of bank failures since it is significant at 1 % significance level in every model. The coefficient is positive which implies that bigger banks are more likely to fail. This finding differs from the findings by Arena (2008) which study Latin America and East Asia. However, this finding might suggest that bigger banks are more likely to receive government aid since banks that both have gone bankruptcy and that have been bailed out are included into my definition of a bank failure. Forgione and Migliardo (2018) also find a positive coefficient for size but the result is not statistically significant.

[7] I also run a model without time fixed or country fixed effects, and the results are significantly better when at least time fixed effects are included.

[8] The bank failure definition that I use, defines that bank is failed if it has received state aid. Because some banks have received state aid several times in different years, they are defined as failed more than once. That creates a problem if bank fixed effects is included.

In addition to size, capitalization is significant in every model. In addition, ROA is slightly significant in three models, but with H-statistics and time fixed effects it loses its significance. The results imply that banks that are better capitalized and have higher earnings are less likely to be failed. These results are consistent with previous results and my hypotheses (Arena, 2008; Čihák & Schaeck, 2010; Lin & Yang, 2016; Poghosyan & Čihak, 2011).

From macroeconomic factors, GDP growth is highly significant determinant of a bank failure since it is statistically significant with both time fixed effects as well as with time and country fixed effects. The results for inflation and interest rate depends on what model specification is used. Inflation is negative and significant when both time fixed and country fixed effects are included whereas interest rate is highly significant when only time fixed effects is included. Results of GDP growth and interest rate are as expected: lower GDP growth and higher interest rate increases a probability of a bank failure. However, unlike in previous research, I find that higher inflation seems to decrease a probability of a bank failure. (Arena, 2008; Demirgüç-Kunt & Detragiache, 2005; Lin & Yang, 2016; Männasoo & Mayes, 2009; Minsky, 1992; Minsky, 1994.)

Both concentration and competition are significant with time fixed effects. However, they lose significance when the country fixed effects are included, and concentration turns from positive to negative. In models 1 and 3 the coefficient for concentration is positive and for competition negative, so, an increase in concentration and a decrease in competition increase a probability of a bank failure. These results are consistent with the results by Poghosyan and Čihak (2011) and Boyd and De Nicolo (2005).

Pseudo-R2 and AIC are measures of model performance. Higher Pseudo-R2 and lower AIC imply that model performs better. Based on these two values, the models with both time and country fixed effects perform better than the models with only time fixed effects. Thus, based on the findings the variables seem to change over time as well as across countries which is why both fixed effects should be added when examining bank failures.

Table 8. The baseline model with HHI or H-statistic.

	Dependent variable:			
	failed			
	(1)	(2)	(3)	(4)
lg_assets	1.112***	1.041***	1.256***	1.054***
	(4.42)	(3.24)	(5.04)	(3.31)
eq_a	-0.189**	-0.167*	-0.160*	-0.165*
	(-2.24)	(-1.76)	(-1.91)	(-1.75)
cir	0.00450	-0.000979	-0.00162	0.000286
	(0.50)	(-0.09)	(-0.18)	(0.03)
roa	-0.860*	-0.821*	-0.816	-0.820*
	(-1.68)	(-1.74)	(-1.49)	(-1.72)
llprov_loan	-0.172	-0.457	-0.0581	-0.502
	(-0.52)	(-1.18)	(-0.17)	(-1.31)
liqa_a	-0.0146	-0.0101	-0.0277	-0.0104
	(-0.85)	(-0.63)	(-1.47)	(-0.64)
gdp_growth	-0.429***	-0.205*	-0.534***	-0.242**
	(-3.83)	(-1.66)	(-3.84)	(-2.00)
inflation	-0.379	-0.435**	-0.526	-0.481**
	(-1.57)	(-2.03)	(-1.52)	(-2.11)
int_rate	1.931***	0.851	1.642***	0.814
	(4.86)	(1.25)	(4.09)	(1.21)
hhi	0.00140***	-0.00119		
	(5.82)	(-1.47)		
h_stat			-2.150**	4.843
			(-1.98)	(0.44)
constant	-10.93***	-6.133**	-7.883***	-8.780*
	(-6.89)	(-3.01)	(-4.43)	(-2.00)
Time fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	No	Yes	No	Yes
N	6,840	5,556	6,840	5,556
Pseudo-R2	0.4036	0.4485	0.3688	0.4459
AIC	316.76	304.21	333.48	303.40
P-value	0.000***	0.000***	0.000***	0.000***
Note:				*p<0.1; **p<0.05; ***p<0.01

Next, I study whether adding GDP per capita growth instead of GDP growth changes the results. Model 1 is the same as Model 2 in Table 8 but GDP growth is replaced with GDP per capita growth. As in previous regressions, I use lagged variables in every model, and because previous results show that models with time and country fixed effects perform better than models with only time fixed effects, I add both fixed effects to all of the following models. The results show that unlike GDP growth, GDP per capita growth does not have a significant effect on a bank failure probability. Furthermore, unlike in previous regression results, concentration is negative and slightly statistically significant. The result implies that higher concentration in fact decreases a probability of a bank failure. The result does not support previous research results (Poghosyan & Čihak, 2011).

In the second model I add another measure of liquidity, total loans to total customer deposits ratio to the first model. Also Forgione and Migliardo (2018) use the same ratio and finds a positive relationship with the ratio and a probability of a bank failure. In contrast, my results imply that increase in the ratio decreases a probability. This might indicate that banks that fail are not earning enough. The result is statistically significant unlike the coefficient of another liquidity measure, liquid assets to total assets.

The third model further adds a domestic credit to GDP ratio. The ratio is positive which implies that a higher amount of credit compared to GDP increases a probability of bank failure. The result is consistent with the theory of banking crises by Hyman Minsky that predicts that banks tend to increase their lending before a crisis (Minsky, 1970, 1992). However, my results do not indicate that domestic credit would have a significant effect on a bank failure probability since the ratio is not statistically significant. Other results do not change much, but concentration becomes insignificant when domestic credit to GDP is added.

In Table 8 I study concentration and competition measures separately because their correlation is quite high. However, as mentioned before, it is not so high that it would create a problem with multicollinearity. Thus, in the fourth model I include both concentration and competition. In this model specification neither variable is statistically significant.

The sign of the competition factor is as expected: higher competition decreases a probability of a bank failure. As in other models in Table 9, the coefficient of concentration is negative and contradicts previous research (Boyd & De Nicolo, 2005; Poghosyan & Čihak, 2011). Other results are similar as in models 1-3.

When Pseudo-R2 and AIC are examined, it is clear that adding total loans to total customer deposits increases a model performance. Thus, the factor contains important information on bank failure probability and should be added to the model. When domestic credit to GDP is included, the performance increases slightly and adding H-statistic does not seem to have any effect on the performance. So, including domestic credit to GDP and both concentration and competition measures is not necessary since they do not have significant effect on the performance of the model.

Table 9. Adding more variables to the baseline model.

	Dependent variable:			
	failed			
	(1)	(2)	(3)	(4)
lg_assets	1.026***	1.316***	1.307***	1.307***
	(3.21)	(3.51)	(3.51)	(3.51)
eq_a	-0.168*	-0.260*	-0.260*	-0.260*
	(-1.79)	(-1.89)	(-1.88)	(-1.88)
cir	-0.00207	-0.0161	-0.0158	-0.0158
	(-0.19)	(-1.04)	(-1.02)	(-1.02)
roa	-0.851*	-1.209*	-1.183*	-1.183*
	(-1.84)	(-1.79)	(-1.72)	(-1.72)
llprov_loan	-0.436	-0.716	-0.702	-0.702
	(-1.14)	(-1.52)	(-1.50)	(-1.50)
liqa_a	-0.00936	-0.0254	-0.0271	-0.0271
	(-0.59)	(-1.35)	(-1.40)	(-1.40)
gdp_pc_gr	-0.157	-0.372	-0.316	-0.316
	(-1.24)	(-1.43)	(-1.38)	(-1.38)
inflation	-0.444**	-0.854**	-0.810**	-0.810**
	(-2.06)	(-2.06)	(-2.31)	(-2.31)
int_rate	0.940	0.922	1.158	1.158
	(1.37)	(0.85)	(0.85)	(0.85)
hhi	-0.00136*	-0.00158*	-0.00148	-0.00148
	(-1.68)	(-1.82)	(-1.62)	(-1.62)
loan_custdeps		-0.00716*	-0.00697*	-0.00697*
		(-1.77)	(-1.77)	(-1.77)
credit_gdp			0.0229	0.0229
			(0.94)	(0.94)
h_stat				-21.54
				(-0.77)
constant	-5.979**	-2.218	-6.028	2.489
	(-2.92)	(-0.72)	(-1.13)	(0.33)
Time fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
N	5,556	5,460	5,460	5,460
Pseudo-R2	0.4460	0.5090	0.5101	0.5101
AIC	305.37	262.75	264.28	264.28
P-value	0.000***	0.000***	0.000***	0.000***
Note:				*p<0.1; **p<0.05; ***p<0.01

Next, I examine how does including factors with no lags, with first lags and with second lags affect the results. In Table 10 Model 1 uses no lags, Model 2 uses first lags, and Model 3 uses second lags. Based on the findings in Table 8 and Table 9, I include GDP growth instead of GDP per capita growth. In addition, I include total loans to total customer deposits ratio but do not include domestic credit to GDP ratio or H-statistics.

As previously found, size seems to be a highly significant factor of a bank failure probability. In addition, capitalization is significant only in the first two models, so, it is able to determine bank failures one year before a failure, but not anymore two years before. Liquid assets is significant in a model with no lags and total loans to total customer deposits in models with no lags and first lags. Thus, liquidity of a bank seems to be able to determine bank failures the best right before a bank fails.

From the macroeconomic factors GDP growth, inflation, and concentration are significant. However, concentration is significant with no lags and cannot determine bank failures one year or two years before a failure. In contrast, GDP growth and inflation have no effect just right before a failure, but GDP growth is highly significant with second lags and inflation with first and second lags. So, unlike bank specific variables, macroeconomic factors seem to be able to determine a bank failure better few years before a failure than just before it.

Overall, it seems that the variables can determine bank failures the best one year before a failure since the second model has the highest Pseudo-R2. More specifically, the model with first lags is able to determine 51.30 % of the failures correctly whereas the model with no lags 47.41 % and the model with second lags 45.73 %. However, AIC is actually the lowest for the first model which suggests that updated data can predict bank failures with less error than lagged data. This result is intuitive, however, supervisors rarely have this kind of data available.

Table 10. No lags, the first lags, and the second lags.

	Dependent variable:		
	failed		
	(1)	(2)	(3)
	No lags	1st lags	2nd lags
lg_assets	1.688***	1.319***	0.799**
	(3.29)	(3.53)	(2.91)
eq_a	-0.270*	-0.263*	-0.106
	(-1.69)	(-1.83)	(-1.21)
cir	0.0118	-0.0149	0.00899
	(0.75)	(-0.94)	(0.59)
roa	-0.226	-1.139	0.236
	(-0.28)	(-1.59)	(0.56)
llprov_loan	-0.252	-0.725	0.166
	(-0.61)	(-1.53)	(0.55)
liqa_a	-0.0558**	-0.0273	-0.0245
	(-2.29)	(-1.42)	(-1.57)
loan_custdeps	0.000228*	-0.00711*	-0.00216
	(1.81)	(-1.79)	(-1.04)
gdp_growth	-0.0954	-0.444	-0.392***
	(-0.46)	(-1.58)	(-2.65)
inflation	-0.267	-0.876**	-0.413**
	(-0.94)	(-2.00)	(-1.98)
int_rate	0.554	0.798	0.973
	(0.55)	(0.71)	(1.10)
hhi	0.00703***	-0.00129	-0.000191
	(2.60)	(-1.47)	(-0.23)
constant	-19.23**	-2.196	-7.785*
	(-2.99)	(-0.69)	(-2.19)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
N	6,104	5,460	5,616
Pseudo-R	0.4741	0.5130	0.4573
AIC	191.34	261.05	341.64
P-value	0.000***	0.000***	0.000***
Note:	*p<0.1; **p<0.05; ***p<0.01		

For robustness, I examine how well only bank specific or only macroeconomic factors are able to determine bank failures. First model in Table 11 includes bank specific factors alone. In the model all of the factors except liquid assets to total assets are significant. Furthermore, results for capitalization, earnings, and liquid assets to total assets are consistent with previous research (Arena, 2008; Čihák & Schaeck, 2010; Lin & Yang, 2016; Poghosyan & Čihak, 2011). However, based on the findings increase in cost to income ratio, loan loss provision to total loans, and total loans to total customer deposits and decrease in size in fact decrease a likelihood of a failure. These findings contradicts the results by Poghosyan and Čihak (2011) and Lin and Yang (2016).

The second and the third models include only macroeconomic factors, and the second model uses GDP growth and the third GDP per capita growth. The results are similar as in previous regressions. When pseudo-R2s and AICs are examined, it can be seen that the model with bank specific factors performs significantly better than the models with macroeconomic factors. However, bank specific factors alone are not able to determine bank failures as well as bank specific and macroeconomic factors together. Thus, as it has been stated in previous studies, both bank specific and macroeconomic factors should be added into a model when determining bank failures. (Arena, 2008; Lin & Yang, 2016; Poghosyan & Čihak, 2011)

Table 11. Bank specific and macroeconomic variables separately.

	Dependent variable:		
	failed		
	(1)	(2)	(3)
lg_assets	1.271***		
	(3.62)		
eq_a	-0.241**		
	(-2.23)		
cir	-0.0220*		
	(-1.80)		
roa	-1.673***		
	(-3.66)		
llprov_loan	-0.669*		
	(-1.88)		
liqa_a	-0.0248		
	(-1.57)		
loan_custdeps	-0.00872**		
	(-2.15)		
gdp_growth		-0.213***	
		(-2.89)	
gdp_pc_gr			-0.174**
			(-2.41)
inflation		-0.337**	-0.362**
		(-2.29)	(-2.48)
int_rate		0.912	0.989
		(1.49)	(1.60)
credit_gdp		0.0230	0.0263*
		(1.58)	(1.82)
hhi		-0.000821	-0.000945
		(-1.21)	(-1.40)
constant	-5.363**	-8.689**	-9.077**
	(-2.89)	(-3.09)	(-3.27)
Time fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
N	5,460	8,370	8,370
Pseudo-R	0.4592	0.3111	0.3083
AIC	276.33	586.22	588.41
P-value	0.000***	0.000***	0.000***
Note:			*p$<$0.1; **p$<$0.05; ***p$<$0.01

6.2 Behavior of bank specific variables before a bank failure

Next, I examine deeper bank specific factors and how they behave before a bank failure. I use the same factors as I used in my regression analysis: total assets, equity to assets ratio, cost to income ratio, return on assets, loan loss provision to total loans ratio, liquid assets to total assets ratio, and total loans to total customer deposits ratio. I calculate average changes and average levels for a time period from four years before a bank failure to a failure year. The values are calculated for every year separately.

Table 12 represents the average changes for five different years. -4 indicates four years before a failure and 0 a failure year. I test whether a change significantly differs from zero, and the corresponding p-value is in the parentheses. Furthermore, Figure 2 visualizes a behavior of the variables. Based on the results, banks tend to increase in size before a failure, but in the failure year total assets of banks drops. The results are statistically significant for every year.

Equity to assets ratio decreases every year before a failure but the change is statistically significant only two years before a failure and in a failure year. The decrease is especially high, 22 %, in a year that a bank fails. Change in cost to income tend to increase before a failure and decrease in a failure year, but the change differs significantly from zero only in two years before a failure. Thus, there are big changes in capitalization and managerial quality already few years before a bank failure, and capitalization tend to drop just before a failure.

Change in ROA is significant in every year before a failure and highly significant four years before a failure as well as in a failure year. More specifically, earnings of a bank start to decrease already four years before it fails and in a failure year it tends to have a significant drop. In the regression analysis ROA was not very significant factor of a bank failure, but these findings suggest that there are significant changes in earnings of a bank before it fails.

Loan loss provisions to total loans ratio increases in every year and the change is significant in every year. Four and three years before a failure the change is low compared to changes later, and in the failure year the asset quality decreases the most. As ROA, also loan loss provisions to total loans seems to change a lot even thought in regression analysis it is found to be significant only in a model with two lags.

Lastly, the two liquidity measures seem to change already several years before a failure. Liquid assets to total assets ratio decreases almost in every year, but the change differs significantly from zero only in four years before a failure. Thus, the most significant changes in the liquidity seem to occur several years before a bank actually fails. The results for total loans to total customer deposits ratio are not as clear as for liquid assets to total assets. The ratio increases first, then it slightly decreases and in a failure year it has a large increase which is however not statistically significant.

Table 12. Average changes before a bank failure.

	-4	-3	-2	-1	0
assets	0.11 (0.002)	0.06 (0.024)	0.11 (0.011)	0.06 (0.053)	-0.04 (0.017)
eq_a	-0.04 (0.344)	-0.04 (0.204)	-0.10 (0.003)	-0.07 (0.196)	-0.22 (0.029)
cir	0.03 (0.369)	0.09 (0.219)	0.08 (0.056)	0.07 (0.108)	-0.03 (0.856)
roa	-0.35 (0.023)	-0.55 (0.045)	-1.21 (0.061)	-1.21 (0.005)	-3.43 (0.023)
llprov_loan	0.40 (0.005)	0.61 (0.029)	2.84 (0.067)	1.17 (0.035)	3.91 (0.001)
liqa_a	-0.16 (0.056)	-0.10 (0.187)	-0.03 (0.774)	0.06 (0.350)	-0.09 (0.176)
loan_custdeps	0.02 (0.253)	0.06 (0.030)	-0.02 (0.408)	-0.07 (0.058)	0.71 (0.371)

Note: The t-test examines whether the change significantly differs from a zero. P-value is presented in the parentheses.

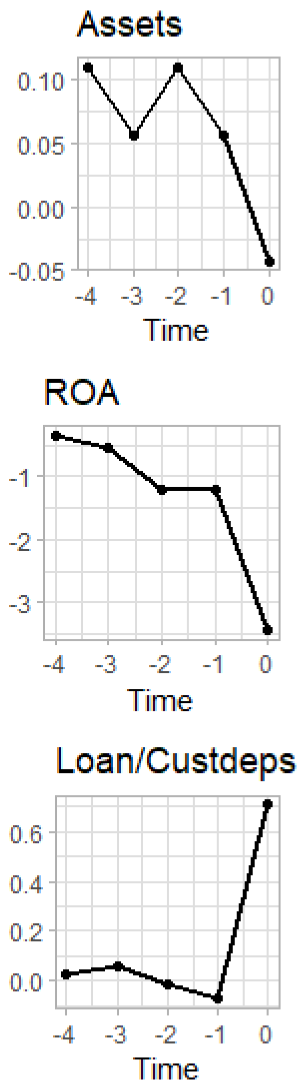

Figure 2. Average changes of bank specific factors before a bank failure.

As a robustness test I calculate also average levels for each bank specific variable. The results are in Table 13, and Figure 3 visualizes them further. Furthermore, I test whether the average values differ from the average of corresponding value of not failed banks. The p-value is presented in the parentheses.

As can be expected based on my previous results, a size of failed banks differs significantly from a size of not failed bank every year. Also equity to assets ratio is lower for failed banks than for not failed banks in most of the years. Since the capitalization is the most significant in a failure year, and results in table 12 show that the ratio also decreases the most in a failure year, it can be concluded that a capitalization tends to e crease significantly just before a bank failure.

Both liquidity measures are lower for failed banks than for not failed banks and they are significant in most of the years. However, findings in Table 12 suggest that neither measure changes significantly before a failure but based on these results their levels are different than the levels of not failed banks'. Furthermore, the difference between failed banks' and not failed banks' total loans to total customer deposits ratio is highly significant in every year. Since previous regression analysis revealed that there is a negative relationship between the total loans to total customer deposits ratio and a probability of a bank failure, failed banks in Europe might have not been earning enough compared to the banks that did not fail.

The average level of cost to income ratio of failed banks differs from the average level of not failed banks' ratio only in one year, and the average of loan loss provisions to total loans ratio does not differ from not failed banks' average in any year. The results are consistent with my previous regression results which show that neither factor is a significant determinant of a bank failure. However, since changes in loan loss provisions to total loans are significant, asset quality tends to change significantly before a failure.

Table 12 shows that ROA tends to decrease every year before a failure. The results in Table 13 indicate that earnings of a failed bank is actually significantly higher than not failed banks' earnings four years before a failure. However, in the following years the level decreases and drops to a negative one year before a failure. So, ROA might be at a good level at first, but as results in Table 12 show, it decreases every year and experiences especially large drops near a failure.

Table 13. Average values before a bank failure.

	-4	-3	-2	-1	0
assets (Milj.)	35532.60 (0.075)	48219.63 (0.024)	156438.33 (0.000)	173160.40 (0.002)	182167.01 (0.005)
eq_a	6.79 (0.302)	6.31 (0.002)	5.15 (0.348)	4.62 (0.066)	2.87 (0.000)
cir	59.96 (0.076)	62.11 (0.668)	62.70 (0.615)	68.45 (0.749)	52.48 (0.197)
roa	0.72 (0.017)	0.52 (0.962)	0.39 (0.902)	-0.33 (0.037)	-2.26 (0.057)
llprov_loan	0.35 (0.931)	0.49 (0.904)	0.66 (0.296)	1.16 (0.262)	3.19 (0.202)
liqa_a	11.30 (0.016)	12.07 (0.075)	15.97 (0.972)	14.78 (0.474)	11.95 (0.004)
loan_custdeps	126.63 (0.000)	139.69 (0.000)	135.78 (0.000)	129.48 (0.000)	287.29 (0.037)

Note: The t-test examines whether the value is significantly different from a corresponding value for banks that have not failed. P-value is presented in the parentheses.

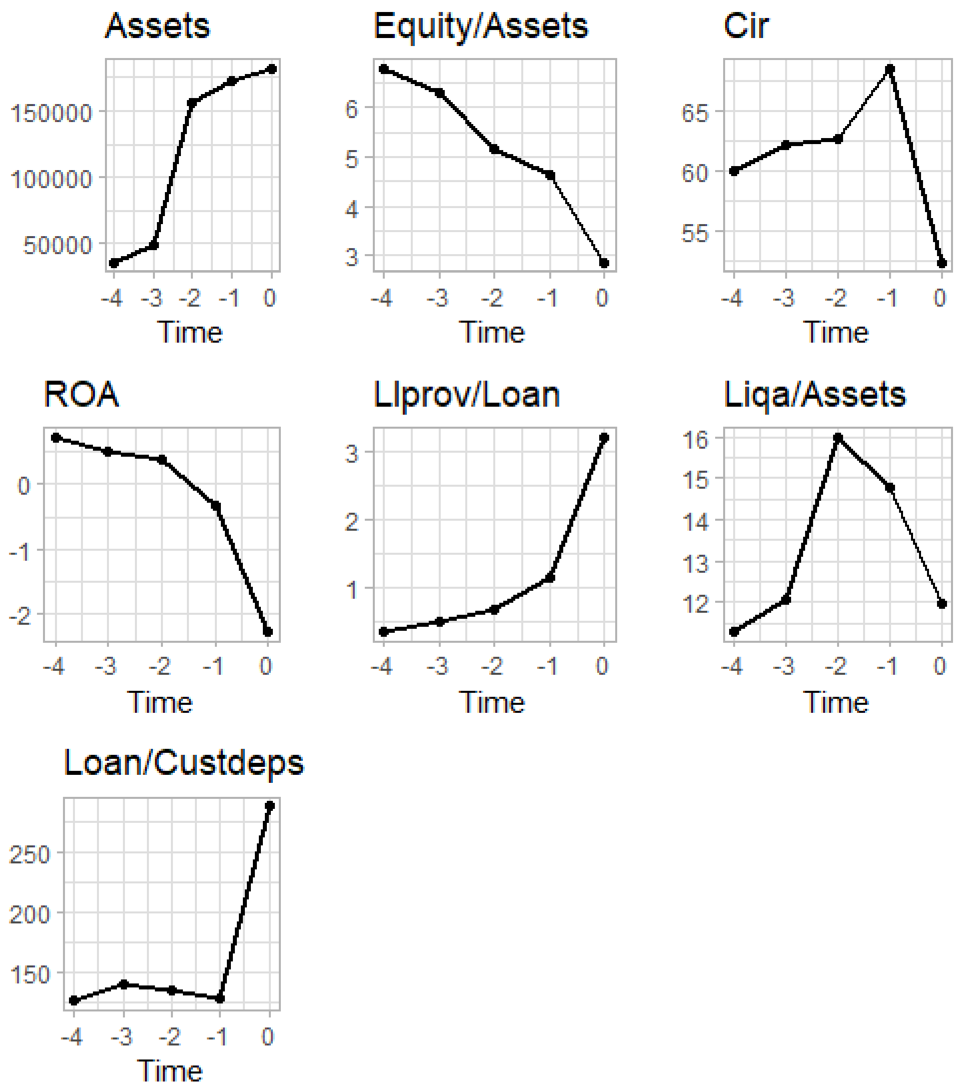

Figure 3. Average levels of bank specific factors before a bank failure.

6.3 Does change in bank specific factors affect a probability of a bank failure?

Next, I run a regression with changes in bank specific variables to study whether changes in the factors are better indicators of bank failures than levels. Table 14 presents the results. First model does not use any lagged variables and the second uses first lags. The model with lagged variables estimates that only change in size is a significant factor of a probability of a bank failure. Increase in size increases a likelihood of a bank failure which is consistent with the univariate results (Table 12). Apart from the results of total loan to total customer deposits, other results are also consistent with univariate results even though they are not statistically significant.

Unlike the model with lagged variables, the model with no lags estimates that almost every variable is statistically significant. Only changes in liquid assets to total assets does not affect a probability of a bank failure which finding is consistent with univariate results. Unlike in the second model, the coefficient of a size is negative which implies that an increase in a change in size decreases a probability of a bank failure. This finding is consistent with results from univariate analysis which show that bank size tends to drop right before a failure.

Finally, the results for capitalization, cost to income ratio, and earnings are not consistent with the results of univariate analysis and previous regression analysis. The regression results in Table 14 suggest that an increase in changes in equity to assets, cost to income and ROA increase a likelihood of a bank failure. However, univariate results show that the variables tend to decrease on a failure year, and regression results in Chapter 6.1. estimate that they have a negative relationship with a probability of a bank failure.

Unlike in previous regressions with levels, Pseudo-R2 is higher for the model without any lags. In addition, AIC is lower for the first model which is consistent with the results with levels. Thus, the results suggest that changes in variables can predict bank failures better with more recent data. Furthermore, Pseudo-R2 is much lower for the models with changes than for the model with levels when only bank specific variables are included. So, it can be concluded that based on these results it would be better to use a model with levels rather than with changes.

Table 14. Changes as independent variables.

	Dependent variable:	
	failed	
	(1)	(2)
	No lags	1st lags
Δassets	-0.0000243**	0.0000115*
	(-2.47)	(1.75)
Δeq_a	0.188*	-0.0368
	(1.84)	(-0.26)
Δcir	0.0397**	0.00492
	(2.40)	(0.40)
Δroa	1.024**	-0.555
	(2.51)	(-1.37)
Δllprov_loan	0.578**	0.199
	(2.23)	(0.69)
Δliq_a	0.0193	0.0132
	(0.69)	(0.50)
Δloan_custdeps	0.000685***	0.0000103
	(3.34)	(0.06)
constant	-6.059***	-5.697***
	(-6.51)	(-5.65)
Time fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
N	4,662	5,179
Pseudo-R	0.3667	0.3543
AIC	171.22	306.44
P-value	0.000***	0.000***
Note:	*p<0.1; **p<0.05; ***p<0.01	

6.4 Predicting failures

In this chapter I predict bank failures using in-sample (2006-2012) and out-of-sample (2013-2018). The purpose of this analysis is to study whether a number of predicted bank failures has decreased since the crisis time. In 2014 Single Supervisory Mechanism came into operation, and its purpose is to harmonize the bank supervision in Europe. In addition, bank regulation has been transformed after the crisis in order to make financial markets more stable. All these measures aim to make European banks more resilient against future shocks.

Table 15 summarizes in-sample and out-of-sample predictions. Because there are seven years in the in-sample and six years in the out-of-sample, I also calculate year means. In addition, I use three different cutoff values: 10 %, 1 %, and 0.1 %.

With every cutoff value, the model[9] predicts less bank failures in out-of-sample than in-sample. When in-sample and out-of-sample year means are compared, the model predicts 77 % less bank failures with 1 % cutoff, but only 8 % with 0.1 % cutoff and 5 % with 10 % cutoff. Thus, bank failures have decreased since the financial crisis 2007-2008. However, since bank failures tend to occur during crises periods, in order to say how new bank regulation and supervision has affected to this decrease, this subject would have to be studied more.

Table 15. Average number of predicted bank failures.

	Nr. of failures		Year mean	
Cutoff	In-sample[1]	Out-of-sample	In-sample	Out-of-sample
10 %	88	17	13	3
1 %	374	287	53	49
0.1 %	1148	927	164	155

[1]In-sample is from 2006 to 2012, and out-of sample from 2013 to 2018.

[9]I use the second model from Table 10 because it has the highest model performance.

7 Conclusions

In this study I research bank failures in EU-12 countries before and after the financial crisis of 2007-2008. I use logit regression and panel data of bank failures between 2006 and 2012 to study how bank specific and macroeconomic factors affect a probability of a bank failure. Furthermore, I study a behavior of bank specific factors in a time period of four years before a failure to a failure year in order to draw conclusions on how the variables change over time. Lastly, a number of predicted bank failures before and after 2012 is calculated to examine whether the number has decreased since increases in bank regulation and supervision. This study contributes to a bank failure literature by examining European bank failures. In addition, this study sheds more light on what happens in banks' balance sheet before it fails.

The results from the determinants of bank failures analysis are mostly consistent with previous studies. However, based on my analysis size seems to be a highly significant factor of a probability of a bank failure and the results suggest that increase in size increases a probability of a failure which is not consistent with the ”too-big-to-fail” hypothesis. The finding might imply that big banks are more likely to get government aid, but due to a data availability, I am not able to draw clear conclusions. Thus, it would have to be researched does the size affect differently a likelihood of a bank getting a bail out than a likelihood of a bank defaulting.

The analysis shows that bank specific factors behave differently during the years before a bank failure. Size, earnings, and asset quality seem to change significantly through the whole time period from four years before a failure to a failure year. However, liquidity decreases significantly only several years before a failure, and capitalization decreases right before a bank fails. Even though total loans to total customer deposits does not change much before a bank failure, it is significantly lower for failed banks than for not failed banks in each year. This finding might imply that European banks are not earning enough which makes them less stable.

The results above show that policy makers and supervisors should focus on different factors when analysing banks. In addition, these findings show that changes in bank specific factors do not occur simultaneously. Furthermore, based on my analysis drop in earnings and asset quality does not necessarily mean that a bank is about to fail soon, but decrease in capitalization is a sign that the bank is in trouble.

Based on the results it can also be concluded that a number of predicted bank failures has decreased after 2012. However, it is not clear whether this change is due to changes in bank supervision and bank regulation or just changes in the economic environment. Fratzscher, König, and Lambert (2016) study 50 developed and emerging countries and find that higher capital buffers and strengthening of supervisory independence have increased a stability of banking markets. Even though the results imply that tightening of bank regulation after the financial crisis of 2007-2008 and harmonization of bank supervision might have enhanced bank stability, the subject would have to be researched more to draw better conclusions.

Lastly, for the stability of the European banking markets, it would be important to get more and better empirical research on bank failures. To achieve this, a complete database of European bank failures would have to be created. This would enable researches to conduct more comparable analysis which would then help policy makers and supervisors to enhance a resilience of European banks.

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Appendices

Appendix 1. Explanatory variables of previous studies

Table A1. Explanatory variables of previous studies.

Study	Data	Significant	Non-significant
Forgione and Migliardo (2018)	Italy; 2007-2012	equity to assets, cost efficiency, profit efficiency, impaired loans, loan to deposit	non-performing loans, earnings, size
Poghosyan and Čihak (2011)	EU; 1996-2007	equity to assets, earnings, asset quality, contagion, concentration	managerial quality, liquidity
Čihák and Schaeck (2010)	100 countries; 1994-2004	ROE, nonperforming loans to gross loans, GDP per capita, M2 to foreign reserves	GDP growth, inflation, interest rate, fiscal surplus to GDP, credit growth
Männasoo and Mayes (2009)	Eastern Europe; 1995-2004	liquidity, equity investments to assets, interest rate, inflation, private lending to GDP	earnings, efficiency, equity to assets, cost to income, loan to assets, GDP growth
Arena (2008)	East Asia; 1995-1999	loans to assets, equity to assets, liquid assets to debt liabilities, ROE, size	loan-loss provisions to loans
Lin and Yang (2016)	East Asia; 1999-2010	equity to assets, asset quality, cost to income, ROA, current assets to assets, GDP growth, M2 to foreign reserves, inflation, interest rate	domestic private credit growth, current account balance to GDP, exports to GDP
Cole and White (2012)	USA	total equity, ROA, nonperforming assets	loan loss reserves, size

Appendix 2. Bank failures by year and country from 2006 to 2012

Table A2. Bank failures by year and country.

	Austria	Belgium	France	Germany	Greece	Ireland	Italy	Luxembourg	Netherlands	Portugal	Spain	UK
2006	1	0	0	0	0	0	0	0	0	0	0	0
2007	0	0	0	0	0	0	0	0	0	0	0	0
2008	0	4	2	2	0	0	0	1	3	0	0	11
2009	1	1	1	1	4	0	0	1	0	0	1	2
2010	1	0	0	0	0	4	1	0	1	0	1	1
2011	0	0	0	0	5	2	0	0	0	0	3	1
2012	0	0	0	0	4	0	0	0	0	3	5	1
In total	3	5	3	3	13	6	1	2	4	3	10	16